In : Lee, Jeffrey A. and Zobeck, Ted M., 2002, Proceedings of ICAR5/GCTE-SEN Joint Conference, International Center for Arid and Semiarid Lands Studies, Texas Tech University, Lubbock, Texas, USA Publication 02-2 p. 127

Extraction of the geometry of surface clasts from ground-based digital images: Application to studies of wind erosion

D.J. MacKinnon, U.S. Geological Survey, Flagstaff (dmackinnon@usgs.gov)

P.S. Chavez, Jr., U.S. Geological Survey, Flagstaff (pchavez @usgs.gov)

Introduction

We are developing a regional dust-emission model for the Southwestern U.S. This model is strongly controlled by the natural suppression of dust-emission by surface roughness and armoring of the surface by clasts and crusts. In our dust-emission study area located in the central Mojave Desert, California, USA, many wind-erosion surfaces are covered by clasts of varying size and coverage density. These clasts suppress wind erosion and dust emission by both physically covering a portion of the erodible surface and by aerodynamically reducing wind stress on portions of the bare surface downwind from each clast. Although the role of clasts and pavement in sheltering a surface against wind erosion is well documented in the literature, little work quantifying the degree of suppression has been done. A quantitative model of this suppression requires not only knowledge about clast number and size, but also clast height above the protected surface. Removing and sieving a surface sample of these clasts destroys the required height information as well as the amount of surface the clasts covered. A method is presented here to extract these critical clast properties using ground-based digital imagery without disturbing the clasts. Final demonstration that the method works will be achieved by comparing image and hand counts.

An on-going study by Dave Miller (pers. comm.) in the central Mojave seeks to examine the effects of a variety of erosion processes on desert slopes. Freeze-thaw and other processes break down native rock into clasts, and eventually long-term creep and sheet-wash transport these clasts to lower elevations. Miller’s study requires the removal and sieving of a large number of surface samples. We have recently joined this study to investigate methods of extracting surface clast and particle size information from digital surface images at Miller’s field sites. In a parallel effort, Pat Chavez is using spatial variability analysis of the digital images to extract clast size statistically. The two studies discussed above would benefit from the automatic extraction of clast properties using digital image processing techniques discussed here.

Methods and Results

We have acquired a large number of digital photographs from a wide variety of central Mojave sites. These images were taken using a 3-megapixel, 3-color digital camera with JPEG compression invoked. The latter digitally smooths the radiance values of the image pixels so that images generally occupy far less memory than the 9 megabytes normally required. We have yet to determine whether such compression reduces the ability of our algorithms to discriminate clasts from their background. Figure 1 shows a black-and-white image of the red band from a 3-color set used to develop the algorithm; note the scale bar in the lower right.

The eye, similar to our algorithm, uses two methods to discriminate an object from its background: color and texture. Our color algorithm generates a processed image by first identifying the 3-color range occupied by the fine-grained, typically uniform background of erodible sediment on which the clasts lie and sets all such pixels to a DN of 255; all other pixels are set to a DN of 0. If the clast colors are clearly different from the background our algorithm does very well at associating a black polygon (as small as a few pixels in size) with the area occupied by each clast in the image (see Figure 2). Discrimination of smaller-sized particles requires another image be taken closer to the surface.

Careful examination of Figure 2 shows that several large clasts remain undetected by the color algorithm because their DN range is similar to the background, however, the eye can easily discriminate these clasts by texture differences. To duplicate the texture discrimination, we created a resultant image by processing each pixel in the original 3-color image with a 9-sample by 9-line standard-deviation box filter. The standard deviation filter measures the degree of DN variability within the box centered on each pixel in the image. In general, background pixels composed of fine-grained material show much higher standard deviation values than do the clasts, which are composed generally of smoother textured clasts. The exception is when a clast is partially covered by fine-grained material or is composed of finely textured (contrasting) materials itself. Our texture-discrimination algorithm was applied to the red band of our test image (Figure 1) and the results are shown in Figure 3. The algorithm clearly shows the red-colored clasts are detected, but detection of the other clasts by this algorithm is poor. Using the color and texture algorithm together promises to yield better overall discrimination than using each one separately.

To optimize the results of either the color or texture algorithm it is important that the images be fully illuminated and contain ***no shadows***; shadows will be falsely classified as a different color and texture than the background surface and counted as part of the clast dimension, and shadows obscure the true size of the clasts.

In the color-processed image (Figure 2) some of the clast locations have “holes” (255 DN) within the 0 DN area associated with a clast or “bridges” between clasts. Further image processing is required to remove these artifacts. The “cleaned-up” image can then be processed by a cluster algorithm to count all pixels associated with a clast. This cluster counting will contain all size and shape information associated with each clast from which a range of statistics can be derived.

Finally, to obtain the clast-height information required for aerodynamic roughness measurements, the clasts need to be illuminated at a low enough elevation angle to display shadows next to the clasts; the low angle illumination can be achieved artificially with a flash unit or using low-sun conditions. From the length of the shadows the height of the clasts can be inferred. The measurement and detection of these shadows can also be automated either by discriminating DN changes between a fully illuminated image and one containing shadows. Another approach to the shadow detection is to use the 3-color images of the scene containing the clast shadows and create a ratio image between the blue and red bands. Because blue light is scattered by the atmosphere more strongly than is red, a blue-to-red ratio image will appear very bright within the location of the shadows and can be readily discriminated. Using the illumination azimuth and elevation angles in the image, the height is extracted by multiplying the largest shadow pixel length for each clast by the tangent of the elevation angle.

All the methods discussed above can be automated to yield the geometry of surface clasts from ground-based images, which greatly simplify and improve the accuracy of surface clasts analysis for all erosion processes.

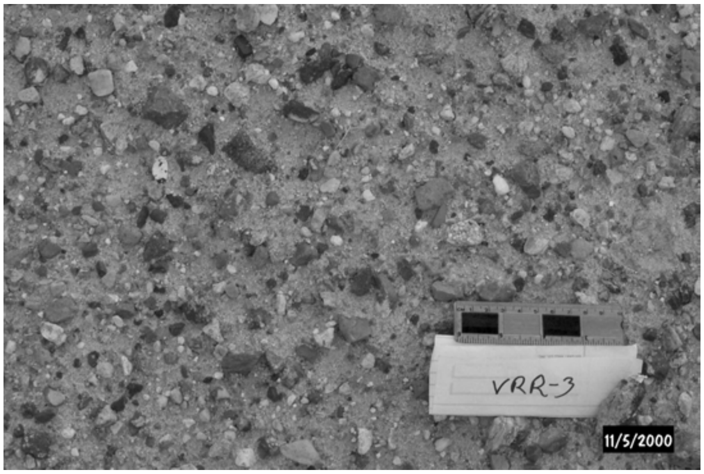

Fig. 1 -- Red band image of ground clasts

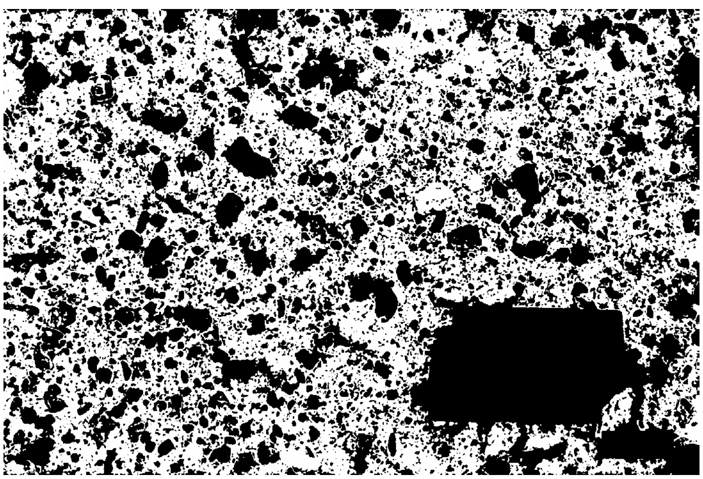

Fig. 2 -- Color algorithm applied to red, green, blue bands

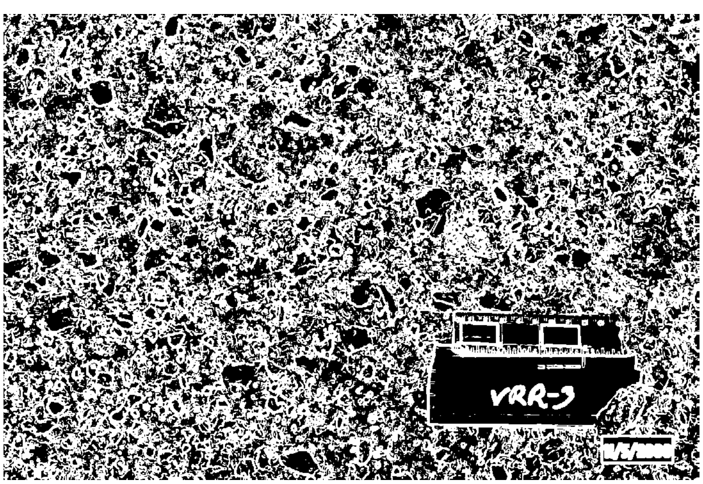

Fig.3—Texture algorithm applied to red band